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Remote sensing and evaluation of the wetland ecological degradation process of the Zoige Plateau Wetland in China

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ABSTRACT

The Zoige Plateau Wetland is the largest high-altitude swamp wetland in China. It plays a key role in ecological balance and the global change. Climate change and improper utilization have consequently resulted in decreased wetland area, disrupted ecosystem structure, and wetland function degradation and function loss. The Zoige Plateau Wetland thus faces severe ecological degradation problems. In this study, selecting the Zoige Plateau Wetland as the study area, remote sensing was used to track the ecological degradation process during 2000–2015 from three aspects (area degradation, structure degradation and function degradation) and at three administrative levels (study area, county and key township). To assess the wetland degradation quantitatively, an analytic hierarchy process (AHP) was used to construct a composite wetland degradation index based on five indicators: wetland area change rate, landscape fractal dimension, landscape fragmentation, vegetation biomass and vegetation coverage. The results showed the following. (1) In terms of area change rate, the total wetland area had continuously decreased during 2000–2015 compared to that in the 1990s, and 2010 was the most significant. The frequency of negative change in the wetland area reached 87.5% in all four counties and across four time periods (2000, 2005, 2010 and 2015), and 85% at the township level. At the spatial scale, Hongyuan County had the smallest wetland area change rate. (2) In terms of structure change, the variations in landscape fractal dimension and landscape fragmentation generally exhibited similar trends at different levels. Specifically, the ecosystem structure was seriously affected in 2000, then gradually recovered in 2005 and 2010, and was again under aggravated interference in 2015. (3) In terms of function change, the above-ground biomass yield in the northeastern region was higher than that in the southern region. A low value was detected in 2000, and then the value increased and remained essentially the same in 2005 and 2010. However, the value decreased in 2015, indicating deteriorated vegetation condition. The vegetation coverage in the study area remained steady, without deterioration in a particular year. (4) In terms of the whole study area, the wetland degradation grades in the four periods were mild (2000), moderate (2005), mild (2010) and mild (2015). In brief, the wetland degradation was the most severe in 2005. Over the 2000–2015 period, the spatial degradation pattern of the Zoige Plateau Wetland progressed from the northeast to the southwest. The model built in this study could be widely applicable. And this study has also some reference value for monitoring and management of wetland degradation by remote sensing.

1. Introduction

Wetlands are not only important components of the global ecosystem (about 6% of the earth's surface area), but are also one of the most important living environments for humans. Wetlands have a multitude of unique ecological functions (including water conservation, wastewater purification and climate regulation) such that they are referred to as the "kidney of the earth" (Sulman et al., 2013; Chatterjee et al., 2015; Beuel et al., 2016). In addition, wetland is one of the important carbon pools (nearly 35% of the total carbon stock of the terrestrial ecosystem), which plays a significant role in the global carbon cycle (IPCC 2014, 2014; Meng et al., 2017). China is rich in wetland resources, with a total area of 53.42×10^6 hm^2 that accounts for 10% of the total global wetland area and 5.58% of the national territorial area of China (Wetland China, 2014).

Due to climate change, social and economic development, and irrational utilization, the total area of wetlands has been decreasing (Sica et al., 2016; Hu et al., 2017), leading to increasingly severe

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degradation, desertification and salinization, decreased river runoff and declined biodiversity (Malekmohammadi and Blouchi, 2014). Over the past 60 years, the coastal wetlands in China have declined by nearly 50%. From 1990 to 2010, China's wetland area had decreased by 8.40 million hm^2. Wetland degradation has become a serious issue, hence it is critical to conduct studies on the status, process and mechanism of wetland degradation.

Wetland degradation occurs under long-term comprehensive impacts of both the natural factors and human activities, eventually leading to the decline in wetland ecosystems, changes in structural stability, and the degradation of natural regulatory functions such as ecosystem stability, resistance and resilience. Consequently, the original ecosystem evolves into another one of low-level state ecosystems. The main manifestations are the loss of wetland area, the decline of structural stability and the decline or loss of natural regulating function (Van Dam et al., 1998; Morton and Barras, 2011; Han et al., 2012). Current research areas of wetland degradation are mainly focused on the microscopic processes and mechanisms of wetland degradation, i.e. analyzing the pedological, biological and ecological mechanisms underlying the changes in soil composition, and in plant and animal communities during the wetland degradation process (Huo et al., 2013; Wu et al., 2015a; Wu et al., 2015b). In the context of climate change, studies on the assessment of wetland degradation using statistical and mechanical models (Malekmohammadi and Blouchi, 2014; Chatterjee et al., 2015), as well as quantitative analyses of the driving mechanisms underlying wetland degradation from different perspectives such as political, economic and social factors (Jiang et al., 2014; Zhang et al., 2015; Nguyen et al., 2017; Ricaurte et al., 2017), have received increasing attention. Long-term monitoring of dynamic changes in wetland resources has become possible with the development of remote sensing technology and the continuous accumulation of remote sensing image data, including multiple remote sensing data from sources such as Landsat MSS/TM/ETM + (Ghobadi et al., 2015; Tulbure et al., 2016; Jin et al., 2017), UAV data (Xia et al., 2017), and SPOT (Davranche et al., 2010), which have been utilized in remote sensing surveillance studies for wetland changes. Presently, researches for wetland degradation are mainly based on single factor analyses (Jiang et al., 2015). However, wetland degradation is a complex, integrated process of wetland area, structure, and function change (Jiang et al., 2014; Liu et al., 2014). It should not be evaluated solely based on the decline in one specific aspect. Considering the status of current studies, there is an urgent need to scientifically analyze and assess wetland degradation from a comprehensive perspective to include the area, structure and function of wetland ecosystems, and especially climate sensitive plateau wetlands (Lam et al., 2018; Lin et al., 2018).

The Zoige Plateau Wetland is located in the northeastern part of the Qinghai-Tibetan Plateau and plays an important role in water conservation and supply, and in ecological balance as well (Bai et al., 2013; Huo et al., 2013). Moreover, the Zoige wetland helps maintain the plateau ecosystem and the global climate environment (Bai et al., 2013). However, due to its relatively fragile ecological environment and accelerated human development activities, a series of ecological problems have emerged. Thus, the degradation of the Zoige Plateau Wetland has drawn wide attention in recent years. At present, research on the Zoige Plateau Wetland degradation primarily focuses on wetland information extraction, wetland and global climate change, degradation characteristics and processes, degradation assessment and remote sensing (Shen et al., 2016). While a few studies have quantitatively described the degradation process, most current studies are qualitative (Yu et al., 2011; Jiang et al., 2015). The analysis currently only involves a single index (Guo et al., 2013), or multiple indices without being analyzed and evaluated comprehensively (Zhang et al., 2012; Gao et al., 2013). In addition, current studies have mostly used a county or a number of counties as a whole for the minimum study analysis of administrative units (Bai et al., 2013). However, wetlands were widely distributed, and wetlands in different regions had great differences in vegetation, water body, landscape pattern and ecological function. The analysis of county as the smallest administrative unit fail to broadly reflect wetland degradation in a larger region.

In this research, selecting the Zoige Plateau Wetland as the study area, remote sensing was used to track the ecological degradation process during 2000–2015 from three aspects (area degradation, structure degradation and function degradation) and at three administrative levels (study area, county and key township). From the perspective of a single index and a composite index model based on 5 indicators, remote sensing and evaluation of the Zoige wetland degradation were carried out quantitatively during 2000–2015. This study has some reference value for monitoring and management of wetland degradation by remote sensing.

2. Study area and methodology

2.1. Profile of study area

The Zoige Plateau Wetland is located in the northeastern part of the Qinghai-Tibetan Plateau and forms the largest plateau swamp wetland in the world (Jiang et al., 2017). In this research, Zoige, Hongyuan and Aba counties in Sichuan, and Maqu County in Gansu were studied (31°50′–34°30′ N and 100°40′–103°40′ E) (Fig. 1a and b). To investigate the wetland change in detail, 18 townships and villages with concentrated wetland distribution were further analyzed as evaluation elements (Fig. 1c). The landform types in the study area include primarily low mountains, hills, river valleys and terraces. The climate is characterized by a typical humid/semi-humid monsoon climate in the continental cold-temperate zone. The annual precipitation is 600–800 mm, and the annual average temperature is 0.96 °C. The average sunshine percentage is 61%, and no season is frostless. The soil types include dark felt-like soil, bog soil, peat soil, felt-like soil and meadow soil, as well as cinnamon soil, new alluvial soil and brunisolic soil. The grassland vegetation types include mountain, alpine and marshy meadows. In addition, there is a small amount of forest vegetation and improved grassland vegetation as well (Zhang et al., 2011).

2.2. Data sources and processing

2.2.1. Data sources

The data used in this study include remote sensing data, surface field data, basic geological data and statistical data. The datasets used in the study area and their sources are shown in Table 1.

The remote sensing data are from Landsat TM/OLI and 16-day integrated MODIS-NDVI data (MOD13). Landsat TM/OLI data, which are from the USGS (United States Geological Survey, http://glovis.usgs.gov/), were used to extract wetland information. The data contains two time points: 1990s and 2015, with a total of 12 scenes. The spatial resolution is 30 m. Taking the amount of cloud cover into consideration, image data taken between July and September were used. The MODIS-NDVI 16-day interval data (MOD13), which are from NASA (National Aeronautics and Space Administration, http://modis.gsfc.nasa.gov/), were used to estimate vegetation above-ground biomass and inversion of vegetation coverage. We used the MOD13 data from June to August in 2000–2015. The spatial resolution is 250 m. Besides, the Google earth images and Gaofen-1 (GF-1) satellite data were extensively used for validation of the classification results.

Field sample data were collected by local grassland departments and administered by the Grassland Monitoring and Supervision Center, Ministry of Agriculture, PRC. Data were collected between June and August each year during 2006–2014, when the vegetation is in the growth stage. For herbaceous plants and short shrubs, the field sample size was 1 m × 1 m. For shrubs and tall herbaceous plants, the field sample size was 10 m × 10 m. The measurements included geographic coordinates, altitude, grass yield, community coverage and community height. Grass yield of herbaceous plants and short shrubs was measured

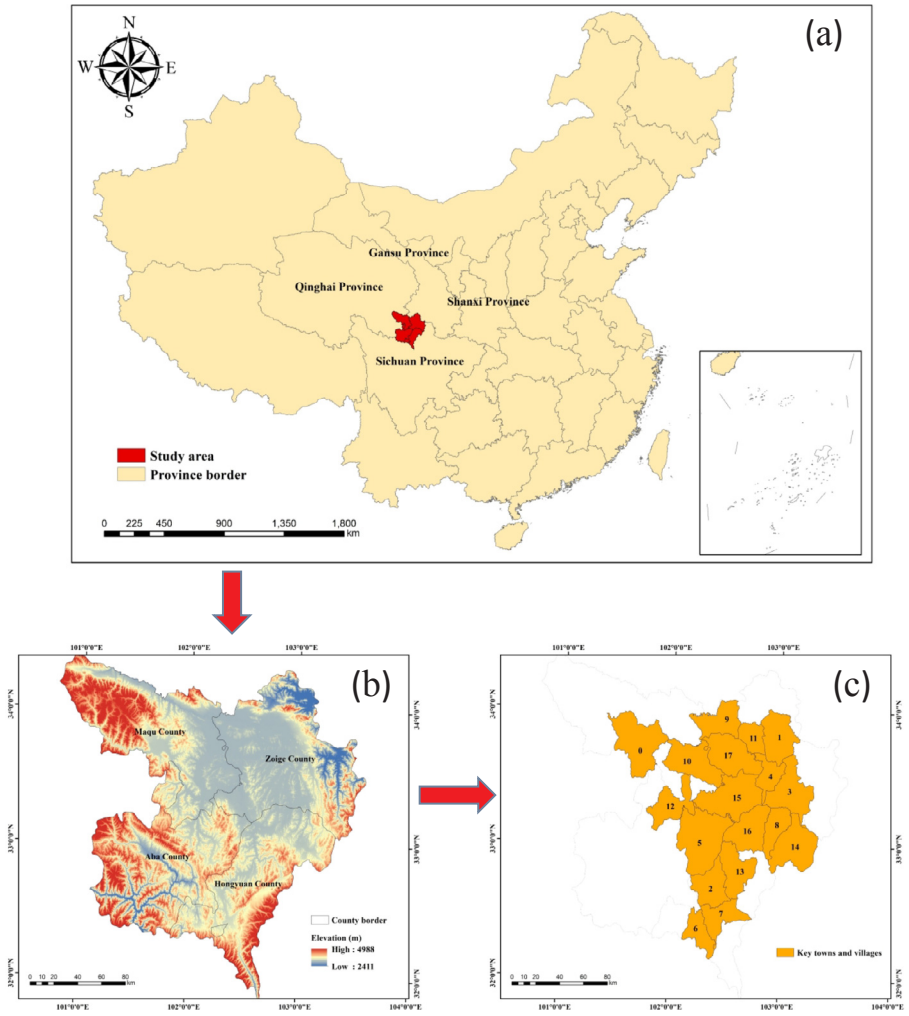

Fig. 1. Location of the study area (a) Study area; (b) Maqu County, Aba County, Hongyuan County and Zoige County; (c) Key townships and villages. 0: Awancang Village; 1: Axi Village; 2: Anqu Town; 3: Banyou Village; 4: Dazhasi Town; 5: Jialuo Village; 6: Jiangrong Village; 7: Longri Village; 8: Maiwa Village; 9: Maixi Village; 10: Manrima Village; 11: Nenwa Village; 12: Qihama Village; 13: Qiongxi Town; 14: Sedi Village; 15: Tangke Town; 16: Waqie Town; 17: Xiaman Village.

by harvesting and weighing the above-ground parts of field sample plants. In terms of shrubs and tall herbaceous plants, grass yield was measured based on the yield and area of a standard field sample plant. The shoots of large, medium and small standard plants of a particular shrub or herbaceous plant type were harvested and weighed, and the weight was multiplied by the number of plants, and then added together, thereby obtaining the grass yield.

The basic geographic data included vector diagrams of the administrative divisions, vector diagrams of the township divisions in the four counties, which were on 1:250,000 scales and the land use data from 2000, 2005 and 2010, which were obtained from the database of the "Ten-Year Evaluation of National Ecological Environmental Change (2000–2010)" (Ouyang et al., 2016). The data accuracy was > 86% (Ouyang et al., 2016), which met the study requirements of this area.

Socioeconomic data (e.g. population and livestock holdings) were obtained from local statistics departments. Surface meteorological data (e.g. precipitation and temperature) were obtained from the website of the China Meteorological Administration (http://cdc.cma.gov.cn).

2.2.2. Data processing

Prior to wetland information extraction, Landsat TM/OLI data were processed (e.g. radiation correction, geometric correction and atmospheric correction) to eliminate possible errors. Based on the Feature Extraction module in the ENVI 5.1 software, the method of combining

Table 1
Datasets used in the study and their sources.

S. No.	Datasets used	Data Source
1	Landsat TM/OLI	Earth Exploration (USGS)
2	MODIS-NDVI(MOD13)	NASA
3	Google Earth images	Google Earth
4	GF-1	China Centre for Resources Satellite Data and Applic http://www.cresda.com/CN/
5	Land use data	Database of the "Ten-Year Evaluation of National Ecological Environmental Change (2000–2010)" http://www.ecosystem.csdb.cn
6	Field sample data	Grassland Monitoring and Supervision Center, Ministry of Agriculture, PRC
7	Socioeconomic data	Local statistics departments
8	Surface meteorological data	China Meteorological Administration http://cdc.cma.gov.cn

object-oriented and Support Vector Machine (SVM) was used to extract the land use information of the study area in 2015, and the wetland spatial distribution information was further extracted. It could distinguish ground objects by statistical analysis of all band information, which did not need to reduce the dimension of data, and had good performance in the aspects of direction convergence, training speed and classification accuracy. Verification samples were selected from high-resolution Google Earth images and Gaofen-1 (GF-1) satellite data, and the extracted wetland information was verified as accurate for application. Since the wetland information in the 1990s was taken as the benchmark year data in this study, the reliability of the data in this period should be guaranteed. In general, visual interpretation accuracy is generally higher than computer classification (Shen et al., 2017). So, man–machine interactive remote sensing image interpretation was used to extract the wetland information of the study area in the 1990s. In order to enhance the display contrast of ground objects, we selected the band combination of 5 (1.55–1.75 μm)/4 (0.76–0.90 μm)/3 (0.63–0.69 μm) to form the RGB image. The interpretation process was performed in ArcGIS 10.0.

A remote sensing inversion model for above-ground biomass was constructed based on the 16-day MODIS-NDVI data and its coupling with the biomass of grassland samples in the same ground location. Details of the data processing method are as follows: the MODIS Reprojection Tool (MRT) was used for the projection, conversion and assembling of images. According to the sample data collection time, the maximum value composite (MVC) procedure was applied to a series of multi-temporal MODIS NDVI data by using the model building module in the ERDAS software. Pixels with NDVI values less than 0.1 were excluded (Zhou et al., 2001). Because the quality of the measured field data is impacted by human factors, which in turn will affect the calibration of model parameters and the accuracy assessment of the model, it is necessary to perform rigorous testing and standardization for the field sample data (Yang et al., 2015). The distance between sample points was calculated to ensure that the distance was greater than 250 m, in order to avoid the overlap of spatial information and data. Based on the field sample data collection time and geographical coordinates information, the average NDVI values within 250 m of every sample point in the NDVI distribution were obtained for each corresponding time period using a GIS spatial analysis technique, and a database of NDVI with its corresponding sample biomass was established.

Considering the remote sensing data used in this study contain two different spatial resolutions (30 m and 250 m), in order to be consistent in data analysis, a bicubic convolution was applied to resample the data to a resolution of 250 m. Besides, the projection coordinate information and geographic coordinate information were edited to make all data unified into the same coordinate system to avoid data analysis errors caused by inconsistent data coordinates.

2.3. Analysis system for the wetland ecological degradation process

In this study, the ecological definition of wetland degradation forms the theoretical basis for the study and by using remote sensing techniques, the analysis system for the Zoige Plateau Wetland ecological degradation process was constructed based on three different aspects (area degradation, structure degradation and function degradation).

2.3.1. Area change rate

The reduction in wetland area is the most direct manifestation of wetland ecosystem degradation, and it is also an important index of wetland degradation. Wetland area change rate reflects the degree of change in wetland area across different years and designates the change in area as a percentage of the original wetland area, which can thereby reflect the wetland degradation rate. Therefore, this study selected the wetland area change rate to characterize the area degradation of the Zoige Plateau Wetland. Wetland area change rate is calculated as follows:

$$RAC = (EA - IA)/IA * 100\% \quad (2.1)$$

where *RAC* is the wetland area change rate; *EA* is the end wetland area (refers to wetland areas in years 2000, 2005, 2010 and 2015); *IA* is the initial wetland area (refers to the wetland area in a specific year or time period with a smaller change in area compared to other years). Through field investigation and consultation with local experts, we learned that large-scale wetland degradation occurred in the Zoige Plateau after 1990s. Therefore, this study considers the 1990s wetland information as the base year data and as such, IA is the wetland area for the 1990s.

2.3.2. Landscape fractal dimension and landscape fragmentation indices

Changes in wetland landscapes play a major role in the ecosystem degradation and wetland biodiversity reduction (Jiang et al., 2015). Studies on the changes in composition, diversity, morphology and spatial distribution of landscape structural units can help us understand the temporal variation of landscape structures (Pickett and White, 1985; Turner and Gardner, 2015). Landscape pattern indices are the most commonly used methods to reflect landscape changes. Therefore, this study uses landscape pattern indices to describe the structure degradation of the Zoige Plateau Wetland. There are a variety of landscape pattern indices which have different ecological significance (Li and Wu, 2004; Li et al., 2011). Furthermore, landscape pattern indices have a size effect, i.e. the same index can show different values under different scales (Turner et al., 1989; Turner and Gardner, 1991; Lausch and Herzog, 2002; Turner and Gardner, 2015). Therefore, it is important to select a landscape pattern index that both characterizes the ecological problems of the study and suits different scales. Using the FRAGSTATS software, we calculated 17 landscape pattern indices across the whole study area, Zoige County, Hongyuan County, Aba County and Maqu County respectively. The landscape pattern indices include class area (CA), patch density (PD), number of patches (NP), fractal dimension (FRAC), etc. Factor analysis was carried out and landscape pattern indices that are representative of the study area and suitable for the ecological condition of each county were selected. Three landscape pattern indices (CA, NP and FRAC) were found suitable for representing the landscape information of both the large area and the smaller regions. Based on the study requirements and the ecological significance of these three landscape pattern indices, NP and PD values are related to landscape fragmentation Therefore, we selected FRAC and landscape fragmentation index (LFI) as the two indicators of landscape pattern change in the Zoige Plateau Wetland. The FRAC was used to quantitatively describe the core area size of the landscape/patches and the raggedness of the boundaries. The closer the FRAC is to 1, the more interference the area receives. The LFI is an important component of landscape heterogeneity. It refers to the degree of landscape fragmentation, and reflects the complexity of landscape spatial structure and to some extent, the degree of interference from human activities. Landscape fragmentation is expressed by Eq. (2.2) as follows:

$$LFI = NP/CA \quad (2.2)$$

where *LFI* is the landscape fragmentation index, *NP* is the number of patches of a specific landscape type in the study area, and *CA* is the class area of the landscape. The larger the *LFI* value, the greater is the degree of fragmentation.

2.3.3. Vegetation above-ground biomass and vegetation coverage

Wetlands possess as many as 18 types of ecological functions. Wetland vegetation is the material basis of wetland ecosystems and this directly reflects the condition of the wetland. It plays a key role in determining the strength of the wetland ecological function. Vegetation biomass and vegetation coverage are two common and very effective indices. Considering the diversity and the regional difference of wetland vegetation and its unique and rich ecological functions, one of the two indicators cannot well represent wetland vegetation and wetland

Table 2
Statistical results of wetland area change rate in 2000–2015 (%).

Region	2000	2005	2010	2015
Zoige County	−34.76	−27.07	−34.74	−20.76
Maqu County	−7.31	16.92	11.82	−44.70
Hongyuan County	−12.84	−44.17	−62.79	−31.39
Aba County	−13.61	−58.11	−57.41	−12.44
Study area	−21.58	−25.94	−35.15	−27.55

function. And the two indicators also represent different ecological meanings. Therefore, these two indices were selected in this study to characterize the function degradation of the Zoige Plateau Wetland. The remote sensing inversion of vegetation biomass was performed by constructing a model of the relationship between the measured biomass and NDVI. After field sample screening, model optimization and accuracy verification, the power function was determined to be optimal for the inversion of vegetation above-ground biomass in the Zoige Plateau Wetland. The root mean square error (RMSE) and the mean relative error (MRE) were 1995 kg/hm^2 and 0.33, respectively.

$$Y = 17560X^{4.6012} \tag{2.3}$$

Where, Y is the vegetation above-ground biomass (kg/hm^2) and X is the NDVI value.

The dimidiate pixel model is widely used for remote sensing estimation of vegetation coverage. Based on the MODIS-NDVI 16-day interval data, a modified dimidiate pixel model was used to calculate the vegetation coverage in the study area and which is expressed by

$$VCD_i = (NDVI_i - NDVI_{soil})/(NDVI_{veg} - NDVI_{soil}) \tag{2.4}$$

where VCD_i is the vegetation coverage of the ith event, $NDVI_i$ is the normalized vegetation index at time i, $NDVI_{soil}$ is the normalized vegetation index of observed pixels that are bare soil (or bare sand), and $NDVI_{veg}$ is the normalized vegetation index of pixels that are completely covered by vegetation.

Due to unavoidable noise in the image, extreme NDVI values do not always represent $NDVI_{soil}$ and $NDVI_{veg}$. As such, when evaluating extreme values, we did not directly use the maximum and minimum NDVI values in the region. Instead, the maximum and minimum values in the 5%–95% confidence interval were selected. The $NDVI_{soil}$ and $NDVI_{veg}$ for each county were determined by partition statistical analysis. After remote sensing inversion, the vegetation coverage data were obtained. Based on the measurement of vegetation coverage in field samples, the accuracy of the inversion results was verified. The correlation between the inverted data and measured data was 0.78, and the RMSE was 0.04.

2.4. Model of wetland ecological degradation assessment

Using the above method, indices characterizing wetland area degradation, structure degradation and function degradation were determined. Based on expert knowledge and previous research (Wang, 2015), as well as the "Technical Specification of Ecological Effects Assessment of Ecosystem Protection and Recovery Projects in San Jiang Yuan Region" (DB 63/T1342-2015, 2015), the analytic hierarchy process (AHP) was carried out to obtain the weights of area degradation, structure degradation and function degradation. The weights of single factor indices were also obtained, including wetland area change rate, landscape fractal dimension, landscape fragmentation, vegetation above-ground biomass and vegetation coverage. Thus, a wetland degradation composite index (WDCI) was established. Specifically, the weights of area degradation, structure degradation and function degradation were 0.5396, 0.1634 and 0.2970, respectively (Eq. (2.5)). In terms of wetland area change rate, landscape fractal dimension, landscape fragmentation, vegetation above-ground biomass and vegetation coverage, the values were 0.5396, 0.0409, 0.1225, 0.1188 and 0.1782, respectively. The WDCI is given by Eq. (2.6).

$$f_{WDCI} = 0.5396 f_{area} + 0.1634\, f_{structure} + 0.2970\, f_{function} \tag{2.5}$$

$$WDCI = 0.5396RAC + 0.0409FRAC + 0.1225LFI + 0.1188VAB + 0.1782VC \tag{2.6}$$

where $WDCI$ is wetland degradation composite index, RAC is the area change rate, $FRAC$ is the landscape fractal dimension, LFI is the landscape fragmentation index, VAB is the vegetation above-ground biomass and VC is the vegetation coverage. Since each index has a different unit, the data were normalized based on the minimum and maximum values to obtain a dimensionless value. Thus, WDCI is dimensionless, and the smaller the value is, the larger is the degree of degradation and the worse the composite ecological condition is.

3. Results

3.1. Remote sensing results of the wetland ecological degradation processes

3.1.1. Area degradation process

The wetland area change rates for the study area in 2000, 2005, 2010 and 2015 were −21.58%, −25.94%, −35.15% and −27.55%, respectively, relative to that in the 1990 s. The negative values indicate that the wetland area was degraded, and the severest condition was observed in 2010 (Table 2). Except for Maqu County, which showed a positive area change in 2005 and 2010, the wetland area change was negative for all counties and across the different periods. With respect to the temporal aspect, the most severe wetland degradation occurred in 2010, with an average change rate of −35.78%. In terms of spatial

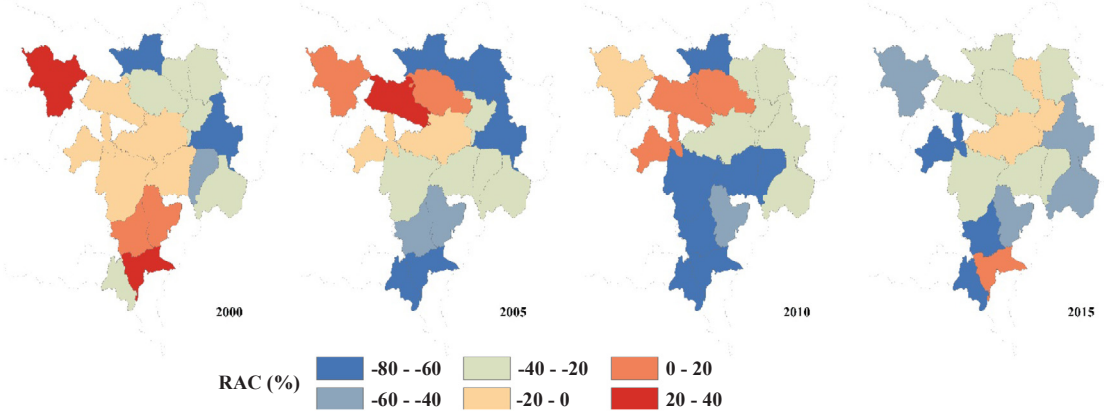

Fig. 2. Wetland area change rate in key townships and villages of the study area.

distribution, Hongyuan County had the smallest area change rate (−37.80%), indicating that its overall wetland ecological condition was worse than other counties (Table 2).

The wetland area change rate in the 18 townships and villages during the 2000–2015 period is presented in Fig. 2. In terms of spatial distribution, regions with severe degradation tended to develop eastward and southward, with Hongyuan County having the most severe degradation. In 2000, townships and villages with a positive area change rate included Awancang, Anqu, Tongxi and Longri. Conversely, townships with severe area degradation (area change rate < −40%) included Maixi, Banyou and Maiwa. In 2005, townships with severe area degradation accounted for 44.44% of all townships, specifically in Zoige and Hongyuan counties. In 2010, townships and villages with a positive area change rate included Manrima, Xiaman and Qihama. Conversely, townships with severe area degradation included Axi, Jialuo, Waqie, Maiwa, Anqu, Hongxi, Longri and Jiangrong. In 2015, only Longri Township had a positive area change rate. Townships with severe area degradation included Awancang, Qihama, Anqu, Hongxi, Jiangrong, Banyou and Sedi. Over the 2000–2015 period, there were 61 (84.72%) counts of negative area change rate in 18 villages and townships. Every township experienced area degradation to varying degrees and degradation was widely distributed.

3.1.2. Structure degradation process

The results of wetland landscape fractal dimension and landscape fragmentation indices for the study area and the four counties are presented in Table 3. In terms of structure degradation in the whole study area, the FRACs in 2000, 2005, 2010 and 2015 were 1.065, 1.136, 1.129 and 1.058, respectively. In general, the FRACs were low, indicating varying degrees of interference from human activities. The interference was low during 2000–2010, but increased during 2010–2015. At the temporal scale, the variation trends in the four counties were similar. In 2000, the FRAC was small (average of 1.066), indicating a large degree of interference. In 2005 and 2010, the FRACs were similar (1.130 and 1.129, respectively), but were higher than that in 2000, indicating decreased interference. However, the interference intensified by 2015 and the average FRAC was 1.058. At the spatial scale, comparisons of the four counties in the same time period showed that the FRACs of Zoige and Hongyuan counties were smaller than that of Maqu and Aba counties. This indicated that the wetlands in Zoige and Hongyuan counties faced more severe interference, which may be related to the rapid development of the local tourism industry in recent years.

The distribution of FRACs in the 18 key townships and villages of the study area from 2000 to 2015 are presented in Fig. 3. It can be seen that the variation trends of FRAC in each township are similar to that of the whole study area. In 2000, the FRAC was small (average of 1.070), indicating a large degree of interference. In 2005 and 2010, the average FRAC reached 1.127 and 1.120, respectively. Thus, the FRAC increased during the 2000–2010 period, indicating a decrease in the degree of interference. However, the average FRAC declined to 1.064 in 2015, indicating increased interference compared to 2005 and 2010. In particular, the FRACs of Nenwa Township were relatively low during the 2000–2015 period, suggesting that the wetland in this region was consistently under strong interference from human activities.

In the whole study area, the LFIs in 2000, 2005, 2010 and 2015 were 0.0423, 0.0029, 0.0033 and 0.0164, respectively (Table 3). In general, the LFIs were small, suggesting that the distribution of wetlands was relatively concentrated. In 2000, the number of wetland patches was the highest, resulting in the largest LFI. From 2000 to 2010, the LFI decreased, but increased again in 2015. The trend of LFI is consistent with the FRAC trend, which indicates that wetland fragmentation was also subject to interference from human activities. Thus, landscape fragmentation can reflect a degree of interference from human activities to some extent. At the temporal scale, the variation trends in the four counties were similar, fragmentation first decreased and then increased. The highest LFI was detected in 2000 (average of 0.0471), indicating a large degree of fragmentation. The LFI decreased significantly over the 2000–2010 period, indicating a concentrated wetland distribution. From 2010 to 2015, the LFI increased. At the spatial scale, Aba County had the largest LFI compared to the other counties, indicating the most severe fragmentation. The distribution of LFIs in the 18 key townships and villages of the study area from 2000 to 2015 are presented in Fig. 4. It can be seen that landscape fragmentation during the entire study period was low, LFIs ranging from 0 to 0.04. In 2000, the LFI was relatively large (average of 0.0518). High LFIs were mainly distributed in Mawa, Sedi and Banyou townships in the southeastern part of Zoige County. The average LFI in 2015 ranked the second highest at 0.0117, followed by similar LFIs in 2005 and 2010 (0.0063 and 0.0074, respectively).

3.1.3. Function degradation process

The results of vegetation above-ground biomass and vegetation coverage in the study area and the four counties are presented in Table 4. In terms of spatial distribution, the above-ground biomass yield in the northeastern part was higher than that in the southern part of the study area. High yields were concentrated mainly in parts of Zoige and Maqu counties. In 2000, the wetland above-ground biomass yield per unit area for the study area averaged 7404 kg/hm^2. The yield increased to 7768 and 7887 kg/hm^2 in 2005 and 2010, respectively, and then decreased to the lowest yield in 2015 at 6907 kg/hm^2. The overall variation trends of wetland above-ground biomass in the four counties were similar, characterized by a relatively low value in 2000, with the lowest value occurring in Zoige County at 5605 kg/hm^2 (13.62% lower than the average). The average biomass remained stable at about 7700 kg/hm^2 in 2005 and 2010. Lastly, 2015 marked a decrease, indicating a deteriorated vegetation condition. In particular, the 2015 yield in Aba County was significantly lower than that in previous periods. Over the 15 year period, the above-ground biomass yield per unit area was the lowest in Aba County (6999 kg/hm^2). This was due mainly to the extremely low yield in 2015. Meanwhile, the yield was the highest in Hongyuan County (7564 kg/hm^2).

In 2000, the wetland vegetation coverage in the study area averaged 0.768, compared to 0.830, 0.759 and 0.801 in 2005, 2010 and 2015, respectively. In general, the vegetation coverage in the four periods was high and stable. The low coverage areas were mainly distributed in parts of Zoige and Maqu counties. Overall, the wetland vegetation coverage in the study area remained stable, without deterioration. In

Table 3
FRAC and LFI results of wetland in 2000–2015.

Region	2000		2005		2010		2015	
	FRAC	LFI	FRAC	LFI	FRAC	LFI	FRAC	LFI
Zoige County	1.063	0.0388	1.126	0.0016	1.129	0.0011	−20.76	0.0074
Maqu County	1.071	0.0187	1.129	0.0025	1.131	0.0024	−44.7	0.0281
Hongyuan County	1.066	0.0555	1.139	0.0056	1.125	0.0115	−31.39	0.0142
Aba County	1.065	0.0756	1.131	0.0084	1.131	0.0075	−12.44	0.0478
Study area	1.065	0.0423	1.136	0.0029	1.129	0.0033	1.058	0.0164

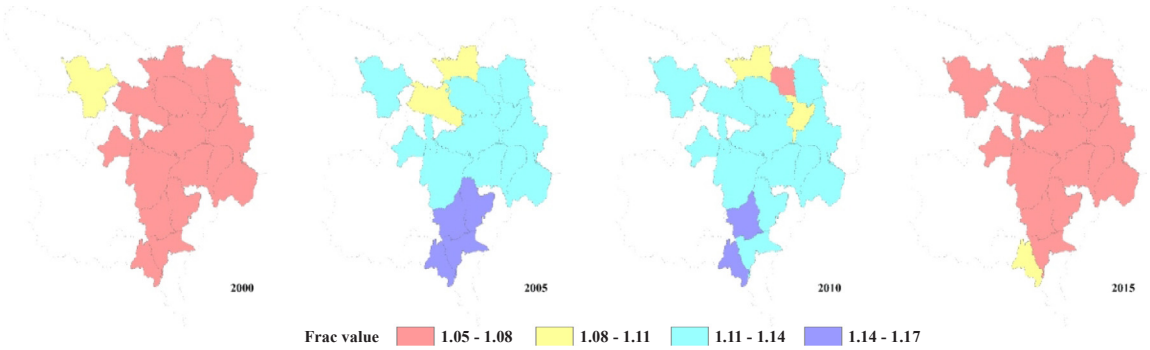

Fig. 3. Distribution of wetland FRAC in key townships and villages of the study area.

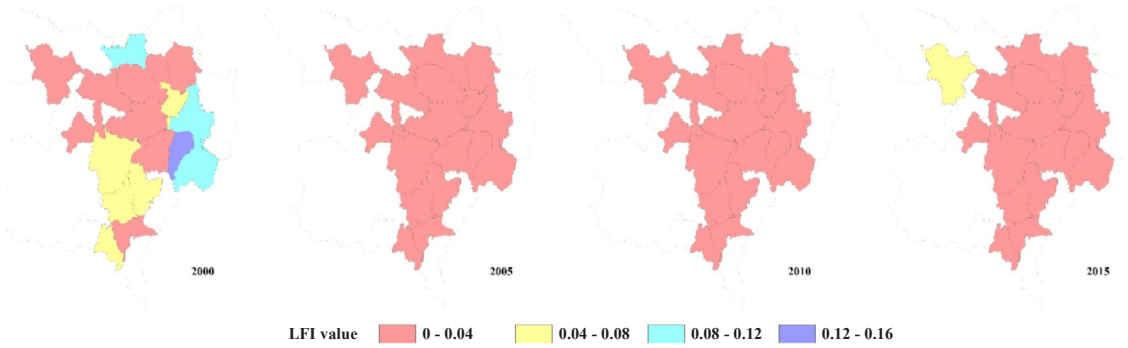

Fig. 4. Distribution of wetland LFI in key townships and villages of the study area.

terms of the four counties, the average values were similar during the 2000–2015 period.

3.2. Assessment of wetland ecological degradation

3.2.1. Temporal variation characteristics of wetland degradation grades

The calculated results for WDCI were divided into four degradation grades by an equal interval method (Uyan, 2014; Glanville and Chang, 2015; Lobatskaya and Strelchenko, 2016; Patriche et al., 2016): severe degradation (0.070–0.265), moderate degradation (0.265–0.460), mild degradation (0.460–0.655) and non-degradation (0.655–0.850). The wetland degradation grades for the whole study area in 2000, 2005, 2010 and 2015 were mild, moderate, mild and mild degradation, respectively. Wetland degradation showed the highest severity in 2005. Among the four counties, Zoige County showed a reversal trend from severe degradation to non-degradation, and its wetland ecological condition gradually recovered. Meanwhile, Maqu County showed a developing trend from non-degradation to severe degradation and for the severe degradation grade, the condition was at its most critical in 2015. Hongyuan County showed moderate degradation in 2010, and non-degradation or mild degradation in all other years. With a severe degradation grade, Aba County showed severe wetland degradation during 2005–2010. At the township level, the degradation trend diversified (Fig. 5). The overall ecological condition of wetlands in Manrima, Sedi, Tangke and Xiaman townships was good, with non-degradation during 2000–2015 or mild degradation in some years. Maixi and Jiangrong townships overall showed wetland degradation of severe or moderate grades. Awancang and Anqu townships showed annual deterioration in wetland degradation grades. Banyou and Dazhasi townships showed an annual decline in wetland degradation and a gradual improvement of the ecological environment.

3.2.2. Area variation characteristics of wetland degradation grades

In 2000, the wetlands in the four counties showed mainly non-degradation or severe degradation, accounting for 62.95% and 37.05% of the total wetland area, respectively. In 2005, the degree of wetland degradation in the four counties was dominated by mild degradation (63.92% of the total wetland area). The proportion of severely degraded wetland decreased to 5.12%, while the proportion of non-degraded wetland decreased to 30.96% (11.40×10^4 hm^2). Compared to 2000, the area of non-degraded wetland decreased by 13.09×10^4 hm^2 in 2005, a 53.47% decrease. In 2010, the four degradation grades were distributed in all four counties. The proportion of non-degraded, mildly, moderately and severely degraded wetlands accounted for 33.88%, 44.81%, 15.35%, and 5.95%, respectively. The area of non-degraded wetland decreased by 0.49×10^4 hm^2 compared to that in 2005, while

Table 4
Vegetation above-ground biomass (kg/hm^2) and vegetation coverage results in 2000–2015.

Region	2000		2005		2010		2015	
	Biomass	Coverage	Biomass	Coverage	Biomass	Coverage	Biomass	Coverage
Zoige County	5605	0.738	7825	0.833	8014	0.764	6962	0.806
Maqu County	6251	0.767	7546	0.828	7970	0.766	6700	0.801
Hongyuan County	7102	0.798	7978	0.839	7835	0.761	7342	0.821
Aba County	6997	0.794	7648	0.831	6977	0.723	6375	0.791
Study area	7404	0.768	7768	0.83	7887	0.759	6907	0.801

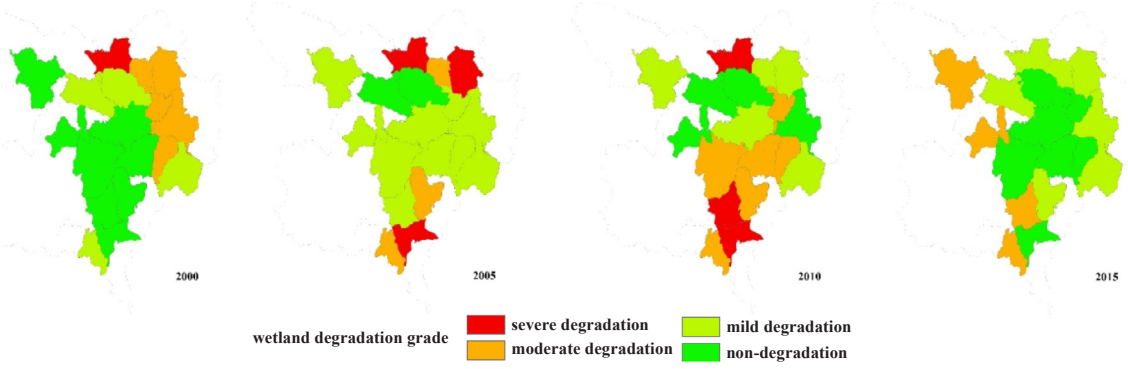

Fig. 5. Wetland degradation grades in key townships and villages of the study area.

the area of severely degraded wetland increased by 312.12 hm^2. The area of mildly degraded wetland decreased by 9.11×10^4 hm^2, which transformed mainly to moderately degraded wetland and non-wetland landscapes. In 2015, the proportion of non-degraded wetland increased to 48.71%, up by 60.63% from 2010. The area of mildly degraded wetland was 13.04×10^4 hm^2, accounting for 36.30%. At 5.39×10^4 hm^2, the area of severely degraded wetland nearly doubled compared to that in 2010. From 2000 to 2015, the area of non-degraded wetland decreased by 6.98×10^4 hm^2, a 28.52% decrease. Meanwhile, the area of severely degraded wetland decreased by 9.02×10^4 hm^2, indicating that the wetland degradation had abated.

In the 18 key townships and villages (Fig. 6), the degree of wetland degradation was dominated by non-degradation in 2000 (51.63%). The proportion of mildly, moderately and severely degraded wetlands accounted for 27.98%, 19.41% and 0.98%, respectively. In 2005, the degree of wetland degradation was dominated by non-degradation (34.57%) and mild degradation (54.37%). The proportion of moderately and severely degraded wetlands accounted for 5.55% and 5.51%, respectively. A comparison between 2005 and 2000 showed that the area of non-degraded wetland decreased by 6.04×10^4 hm^2, a 36.72% decrease. In terms of degraded wetland, the area of moderately and severely degraded wetlands increased significantly by 83.58% and 433.06%, respectively, suggesting that the wetland degradation had accelerated. In 2010, the area of non-degraded wetland accounted for 45.62% of the total wetland area. The areas of mildly, moderately and severely degraded wetlands were 9.19×10^4 hm^2 (33.90%), 4.54×10^4 hm^2 (16.76%) and 1.01×10^4 hm^2 (3.72%), respectively. A comparison between 2010 and 2005 showed that the area of non-degraded wetland increased by 1.96×10^4 hm^2. In terms of degraded wetland, the area of mildly and severely degraded wetlands decreased, while the area of moderately degraded wetland increased significantly by 172.07%. In 2015, the degree of wetland degradation was dominated by non-degradation (56.60%). The proportion of mildly and moderately degraded wetlands accounted for 38.20% and 5.20%, respectively. Wetland areas with severe degradation were not detected.

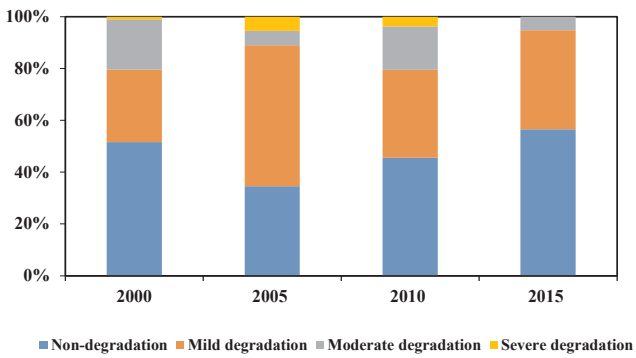

Fig. 6. Proportional distribution of degraded wetland areas in key townships and villages of the study area.

3.2.3. Spatial variation characteristics of wetland degradation grades

In order to further investigate the dynamic spatial variation and pattern of the Zoige Plateau Wetland degradation over the 15-year period, a numeric value was assigned to each degradation grade (Table 5). Based on the difference analysis of the degradation grade shifts across the different periods, the wetland degradation status was categorized (Table 6). For non-degradation, mild, moderate and severe degradation, values of 1, 2, 3 and 4 were assigned to the respective categories. In terms of degradation grade shifts, “developed” refers to an increase in degradation grade, while “seriously developed” refers to an increase of two or more grades. Conversely, “reversed” refers to a decrease in degradation grade, while “significantly reversed” refers to a decrease of two or more grades. Finally, “stable” refers to no change in degradation grade.

In terms of spatial variation, Zoige County showed a “significant reversal” of wetland degradation during 2000–2015, while Maqu County showed a “serious development” trend. In terms of reversal trends, Hongyuan County shifted from “seriously developed” to “reversed”. Aba County shifted from “seriously developed” to “significantly reversed”, with 2010 being the turning point. The spatial variation of wetland degradation in the 18 key townships and villages from 2000 to 2015 is presented in Fig. 7. It can be seen that there was no “significant reversal” in the degree of degradation during 2000–2005. The townships with the “reversed” status mainly included Manrima, Xiaman, Dazhasi, Banyou and Maiwa townships. Wetland degradation in Maixi, Nenwa and Sedi townships remained “stable”. Those with the “seriously developed” status included Hongxi, Longri and Jiangrong. Those with the “developed” status included Awancang, Axi, Qihama, Tangke, Jialuo, Waqie and Anqu. During 2005–2010, wetland degradation was “significantly reversed” in Axi Township. Townships with the “reversed” status included Banyou, Nenwa, Qihama and Jiangrong. Those with the “stable” status included Tangke, Manrima and Awancang. The areas where wetland degradation was “developed” or “seriously developed” were mainly distributed in the central region, including Anqu, Waqie, Maiwa and Dazhasi townships. Specifically, wetland degradation in Anqu Township was “seriously developed”. During 2010–2015, most townships showed a trend of “reversal” and even “significant reversal”. Only Qihama, Awancang,

Table 5
Degradation types and values in study area.

Non-degradation	Mild degradation	Moderate degradation	Severe degradation
1	2	3	4

Table 6
Degradation transform classification in study area.

Significantly reversed	Reversed	Stable	Developed	Seriously developed
≤-2	−1	0	1	≥2
3→1	2→1	1→1	1→2	1→3
4→1	3→2	2→2	2→3	1→4
4→2	4→3	3→3	3→4	2→4
		4→4		

Manrima and Banyou townships still showed a “development” or “serious development” trend. During 2000–2015, wetland degradation in the central townships remained “stable”. Townships in Zoige County showed a “reversal” or “significant reversal”, indicating a decrease in wetland degradation. However, townships in southern Hongyuan County, Qihama Township in Aba County and Awancang Township in Maqu County showed a “development” or “serious development” trend. In brief, the Zoige Plateau Wetland degradation over the 2000–2015 period developed from the northeast to the southwest.

4. Discussion

4.1. Driving forces of wetland degradation

It is commonly accepted that the combined effect of climate change and human activities is an important factor in the formation and development of wetland degradation (Hu et al., 2017). Due to many factors potentially affecting wetland degradation, the dominant factor of wetland degradation is still debatable. Grey relational analysis is a quantitative method for measuring the degree of correlation between different factors. It can be used to quantitatively analyze dynamic development processes, and it is applicable to studies with any sample size and samples with or without regularity. Moreover, the calculation volume is small, but conditions such as inconsistency between quantitative and qualitative analyses are not introduced (Liu et al., 2004). Using grey relational analysis in the calculation of the correlation between wetland area and each index, the contribution of each index to wetland degradation can then be quantitatively determined. Taking data integrity into consideration, Zoige County was selected as the study object. Specifically, quantitative statistics of Zoige County was analyzed by grey relational analysis to discuss the driving forces of wetland degradation. Vegetation growth is closely related to water and heat conditions. Thus, annual precipitation and annual average temperature were selected as the natural factors. Drainage and dewatering have a large impact on the degradation of the Zoige Plateau Wetland. Since the 1960 s, an area of wetland in Zoige County alone of about 1.0×10^5 hm^2 was drained and transformed into grassland or farmland. Therefore, farmland area is an important factor in the analysis of driving forces. Moreover, the study area is rich in tourism resources, including the Zoige Wetland Nature Reserve and the Huahu scenic area. In the development of the tourism industry, the increase in the number of tourists and the construction of public facilities will inevitably have an impact on the natural ecological environment. Therefore, the number of tourists and highway mileage were considered as two factors of wetland degradation. We obtained quantitative data of natural and socioeconomic factors for Zoige County from 2000 to 2015 (Table 7). Specifically, the natural factors included annual precipitation (mm), annual average temperature (°C), and the socioeconomic factors including population, GDP, farmland area (hm^2), large livestock population, highway mileage (km) and tourist population. Of note, the tourist population here represents the tourist population of the entire Aba Tibetan and Qiang Autonomous Prefecture in Sichuan Province.

The calculation of grey correlation includes five steps: calculating the initial value of each sequence, calculating the difference sequence, calculating the maximum and minimum difference, calculating the correlation coefficient and calculating the degree of correlation (Liu et al., 2004). The results show that the correlation between each factor and wetland degradation is high (Table 8). In terms of socioeconomic factors, the descending order of the correlation is as follows: population, large livestock population, farmland area, highway mileage, tourist population and GDP. Thus, the rapid increase in population and livestock were the main socioeconomic driving factors of wetland degradation. In terms of the natural factors, annual precipitation made a larger contribution to wetland degradation than annual average temperature.

4.2. Reliability of the wetland ecological degradation assessment model

In this study, the WDCI results were obtained using remote sensing methods, an assessment system of plateau wetland degradation was established, and large-scale surveillance of the plateau wetland degradation status has been realized. The applicability and reliability of a model is fundamental to its wide application. Therefore, it is necessary to investigate the wetland degradation study results based on WDCI monitoring as reported in this study.

Feng et al. (2015) analyzed the spatiotemporal patterns of vegetation degradation in the Zoige region during 2000–2013 using vegetation coverage indices. The results showed that, with 2008 as a turning point, the vegetation degradation intensified during 2002–2008. After 2008, vegetation degradation was partly under control in some locations and intensified in other locations. In the current study, nearly every index showed a turning point at around 2010. The temporal degradation trends in both studies are consistent. In terms of spatial variation, the Feng et al. study showed a northward development of vegetation degradation in the Zoige region during 2000–2013 and the area of severe degradation gradually shifted from Hongyuan County to

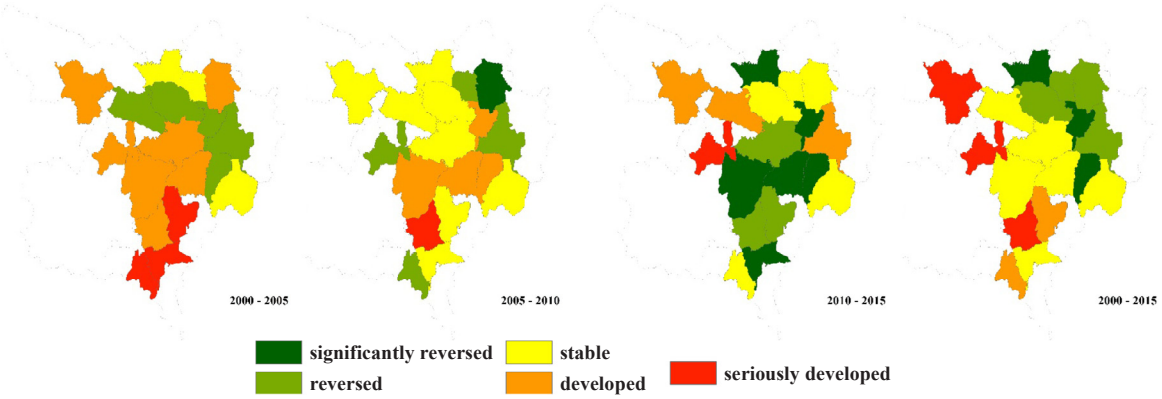

Fig. 7. Spatial distribution of wetland degradation in key townships and villages of the study area.

Table 7
Statistical data of Zoigê County in 2000–2015.

Year	Population (count)	GDP (millin Yuan)	Farmland area (hm^2)	Large livestock population (count)	Highway mileage (km)	Tourist population (million)	Annual precipitation (mm)	Annual average temperature (°C)
2000	64,075	21,779	4725	458,945	702	46.21	592.4	1.27
2001	65,444	22,832	4743	449,315	1100	57.48	593.1	1.70
2002	65,923	24,943	3664	435,723	678	66.72	543.2	1.52
2003	66,551	26,899	2775	511,199	1100	45.09	761.6	2.31
2004	66,504	36,521	2934	517,224	1100	96.62	652.1	1.53
2005	69,882	41,919	3075	526,379	1100	106.28	663.5	2.05
2006	70,283	47,092	3086	537,553	640	140.18	526.3	2.59
2007	71,850	55,899	3089	544,189	816	170.87	609.6	2.08
2008	73,353	59,674	3714	521,041	1105	69.95	464.8	1.68
2009	74,602	73,062	4006	501,997	1145	84.99	567.1	2.55
2010	75,791	85,127	4162	459,478	971	104.93	849.3	2.76
2011	76,477	99,942	4162	455,557	1154	163.97	702.8	2.30
2012	80,000	116,062	4243	446,259	1265	227.33	746.6	2.55
2013	77,900	130,460	4121	408,661	1265	209.56	768	2.80
2014	78,400	139,128	4202	364,072	1265	240.17	717.4	2.77
2015	78,100	153,687	4172.38	304,764	1230	273.2	539.9	2.68

Table 8
Correlation degree results.

Population	GDP	Farmland area	Large livestock population	Highway mileage	Tourist population	Annual precipitation	Annual average temperature
0.980	0.654	0.930	0.958	0.899	0.698	0.945	0.833

Maqu County. This trend in the Feng et al. study is consistent with the results found in this study (Figs. 5 and 7). Jiang et al. (2017) set up a degradation risk assessment system based on multiple indices and analyzed the degradation risks in the Zoige Plateau Wetland from 2000 to 2014. The results showed that the low degradation risk areas in 2000 were distributed in the southwestern and northeastern regions, while the high risk areas were distributed in the northwestern boundary of Zoige County. In the same study area as the current study, the wetland degradation in 2014 was mainly of low risk, with higher risk localized in Maqu County. The distribution of various wetland degradation risk levels and the spatiotemporal trends in the Jiang et al. study are consistent with the wetland degradation grade distribution and variation trends reported in the current study. Taken together, the WDCI model established in this study is suitable for the assessment and analysis of wetland degradation processes. Moreover, the data used for each index were all derived from remote sensing data without data source heterogeneity, hence the model could be widely applicable.

5. Conclusions

Based on aspects of changes in the area, structure and function of wetland ecosystems, the Zoige Plateau Wetland was investigated at the study area, county and key township levels such that the wetland ecological degradation process was monitored during 2000–2015, and a WDCI model was established to assess the wetland degradation quantitatively. This study has some reference value for monitoring and management of wetland degradation by remote sensing.We have reached the following conclusions.

(1) Five indices (RAC, FRAC, LFI, VAB and VC) were selected to represent the degradation in wetland area, structure and function in the Zoige Plateau.
(2) In terms of wetland area degradation, the total wetland area (in the study area) had decreased during 2000–2015 compared to the total wetland area in the 1990 s, and 2010 was the most significant (with an average RAC of −35.78%). The wetland area change rate was negative in 87.5% of all four periods and across all four counties, and 85% at the township level. At the spatial scale, the wetland RAC in Hongyuan County showed the smallest average value at −37.80%. In terms of area variation, the wetlands in the Zoige Plateau showed various levels of degradation during 2000–2015.
(3) In terms of wetland structure degradation, the FRAC in 2000 was small. The FRACs were similar in 2005 and 2010, the values increased and the degree of interference was relieved. The FRAC decreased in 2015 and the degree of interference increased. In the same period, the FRACs of Zoige and Hongyuan counties were less than that of Maqu and Aba counties. The LFIs decreased significantly during 2000–2010, indicating a gradual concentration in the distribution of wetlands.
(4) In terms of wetland function degradation and in the aspect of spatial distribution, the vegetation above-ground biomass yield in the northeastern region was generally higher than that in the southern region. High VAB values were mostly concentrated in parts of Zoige and Maqu counties. The VAB was relatively low in 2000. In 2005 and 2010, the VABs were similar and were up from 2000. However, the VAB was the lowest in 2015, indicating a deteriorated vegetation condition. From 2000 to 2015, the average VAB was the lowest in Aba County (6999 kg/hm^2) and the highest in Hongyuan County (7564 kg/hm^2). The wetland vegetation coverage in the study area remained stable during 2000–2015 and deterioration was not detected in any particular year.
(5) In terms of the whole study area, the wetland degradation grades in 2000, 2005, 2010 and 2015 were mild, moderate, mild and mild, respectively. The wetland degradation trends within the four counties were different. Zoige County showed a trend of “significant reversal”, while the wetland degradation in Maqu County showed a “serious development” trend. Hongyuan County showed a reversal trend from “seriously developed” to “reversed”, and with a significant change. Aba County shifted from “seriously developed” to “significantly reversed”. The inference from the findings for the 18 key townships is that the process of wetland degradation in the Zoige Plateau advanced from the northeast to the southwest over the 2000–2015 period.

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